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Incentive Policies for Facilitating Knowledge Sharing in an Enterprise Social Network

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Abstract:

This paper examines knowledge sharing in enterprise social network (ESNs) through an analytical model. The structure of an ESN, its underlying technology, and incentives for knowledge workers affect knowledge sharing in organizations. We present a stylized model with two groups of knowledge workers with different knowledge levels. High-knowledge workers vary in their connectivity and sharing costs. We explore the design and efficacy of various incentive policies to facilitate knowledge sharing in ESNs. The different incentive schemes target either specific workers or groups based on connectivity, efficiency, or both. Our research provides valuable insights for practitioners to design incentive policies for promoting knowledge sharing in ESNs.

Keywords: Enterprise Social Network, Incentives, Knowledge Sharing.

Felix Ter Chian Tan acted as the senior editor for this paper.

1 Introduction

Many organizations adopt enterprise social networks (ESNs) because they have significant economic advantages (Jackson, 2007). Leonard (2014) reports that primarily middle-level employees use ESNs in areas such as accounting, sales, marketing, human resources, and customer services across different industries including financial services, retailing, manufacturing, hospitality, and healthcare. Leonard also predicts that the number of ESN users will reach 535 million by 2018. In recent years, we have seen organizations increasingly adopt ESNs and use them as the primary tool for team communication and collaboration (Cardon & Marshall, 2015).

Many companies have adopted ESNs, which differ from external social networks such as Facebook, for specific purposes (Trees, 2013). For instance, IBM developed an ESN called Beehive (later called SocialBlue) to help employees connect with their current and past coworkers and share ideas (DiMicco, Geyer, & Dugan, 2005). Capgemini implemented Yammer as its ESN to allow employees to do the same (Riemer, Overfeld, Scifleet, & Richter, 2012). The ESN that KPMG uses allows its workers to quickly obtain answers to their questions from around the world and create new connections with others (O'Leary, 2016).

Among the many uses of ESNs—such as solving problems, exchanging ideas, discussing work-related issues, and managing tasks (Mäntymäki & Riemer, 2016)—knowledge sharing has emerged as an important and common theme. Due to the growing popularity and success of applying social networks in knowledge management, emerging research has started to explore the relationship between ESNs and knowledge sharing in organizations. ESNs facilitate different aspects of knowledge sharing. For instance, an ESN's structure (Luo, Du, Liu, Xuan, & Wang, 2015) and underlying technology affects knowledge sharing in organizations (Jarrahi & Sawyer, 2013). Fulk and Yuan (2013) briefly refer to the use of incentives to motivate knowledge sharing.

Although the literature has identified factors that affect knowledge sharing, it has not studied the role of incentives in ESNs in detail. In a different context, Sundaresan and Zhang (2016) explore the use of incentives in motivating workers to share knowledge. They identify these incentives as an important dimension in designing knowledge management systems to facilitate knowledge sharing (Ba, Stallaert, & Whinston, 2001). Siemsen, Balasubramanian, and Roth (2007) argue that effective knowledge management requires both group and individual incentives. Business practice also provides several examples that illustrate using various incentives to improve knowledge sharing in ESNs. For instance, Lenovo rewards users of its ESN—its "Lenovo Social Champions"—with points in exchange for various actions, including knowledge sharing (Pearson, 2015). Bluewolf, an IT outsourcing and consulting company, incentivizes collaboration in its ESN with prizes and badges. After implementing such incentives, Bluewolf reported a 57 percent increase of collaboration in its ESN (Chui et al., 2012). As part of its "Proven Practice Replication" program, Ford provides recognition for entire departments—a type of group incentive (APQC, 2010). Hence, organizations clearly have much interest in employing both individual and group incentives to facilitate knowledge sharing in their ESNs. However, few academic studies have explored the use of incentive schemes in facilitating knowledge sharing in ESNs. In this paper, we address this gap—the use of individual and group incentive schemes to motivate knowledge sharing in ESNs—and study the efficacy of such incentive schemes.

Contribution:

This research analyzes the problem of designing incentive schemes to promote knowledge sharing in ESNs. Unlike prior research, the proposed group incentive schemes explicitly include ESN features and knowledge worker characteristics. Specifically, we:

- Develop a stylized model that captures essential elements of ESNs' structure, knowledge workers characteristics, and incentives.
- Demonstrate how to design both individual and group incentive policies and develop an algorithm to implement the individual incentive scheme.
- Design group incentives based on connectivity and efficiency of workers, which prior research has not yet investigated.
- Show the conditions under which five different types of group incentives perform the best.

Knowledge management researchers and practitioners should find interest in our research and results. While providing building blocks to study more complicated models, our research can guide empirical research hypotheses. Practitioners can find direct implementable guidelines for group incentive policies.

Specifically, we examine the following research questions: “How should companies design incentive schemes for individual knowledge workers to facilitate knowledge sharing in an ESN?”, “How can these individual policies be extended to group incentives?”, and “How do these group incentive schemes perform under different ESN structures?”.

We develop an analytical model to examine these questions. Using a network representation of ESNs that shows the connectivity among workers, we also capture the elements of incentive schemes along with the efficiency of knowledge workers. Our stylized model incorporates two groups of knowledge workers with different knowledge levels: high-knowledge workers and low-knowledge workers. High-knowledge workers vary in their connectivity and share their knowledge. The analytical model permits one to explore individual and various group incentive schemes.

With our research, we make several contributions. First, we develop a simple algorithm to find a solution to the optimization problem of designing individual incentives. Second, we propose and explore five group incentive policies that reward knowledge workers based on different combinations of connectivity, efficiency, or both. Third, we show the different conditions under which each of these policies performs best. For instance, we demonstrate that, as more low-knowledge workers connect to efficient high-knowledge workers, rewarding efficiency tends to achieve better results. Similarly, as the high-knowledge workers share more common followers, it may be better to reward both efficiency and connectivity.

The rest of the paper proceeds as follows. In Section 2, we review the prior literature on ESNs, knowledge sharing, and incentives. In Section 3, we present our analytical model of knowledge sharing in ESNs. In Section 4, we discuss our analysis and results. In Section 5, we conclude the paper. Readers can find all proofs in the Appendix B.

2 Literature

We review prior literature closely related to our research. A recent survey paper (Wehner, Ritter, & Leist, 2017) classifies existing research on ESNs as having either an individual, technical, or organizational focus. In particular, the paper identifies the impact that ESNs have on knowledge management as an important research area. In this section, we summarize the major findings from previous studies that contain elements of ESNs, knowledge sharing, and incentives in their research framework under the following three themes: 1) goals and success factors of ESNs, 2) knowledge sharing in ESNs, and 3) incentives for knowledge sharing. Finally, we highlight how our paper fills the lacuna of research on the use of individual and group incentive schemes to motivate knowledge sharing in ESNs.

2.1 Goals and Success Factors of ESNs

Employees typically use ESNs in organizations to self-organize and fulfill information needs such as solving problems, exchanging ideas, discussing work-related issues, managing tasks, obtaining updates, and chatting informally (Mäntymäki & Riemer, 2016). Razmerita, Kirchner, and Nabeth (2014) observe that ESNs help individuals and organizations to manage personal and collective knowledge through a synergistic approach, and they can mutually reinforce each other. ESNs blur the boundary between work and social life for employees and, thereby, generate positive reinforcement in using them (Kock, Gonzales, & Leidner, 2012). ESNs may contribute to problem solving in organizations, and whether employees engage in them depends highly on the activities they perform on them (Mettler & Winter, 2016). In particular, one can attribute the success of an ESN in an organization to three categories of employee competence factors: knowledge, skills, and attitude. Richter, Hetmank, Klier, Klier, and Müller (2016) identify one particular factor in the attitude category—that workers tend to keep their knowledge secret and not share it—as a significant obstruction to ESN success. Although ESNs serve many purposes in an organization, we highlight their role in knowledge sharing in particular in Section 2.2.

2.2 Knowledge Sharing in ESNs

Technological, organizational, social, and individual factors highly influence how employees use ESNs to share knowledge (Chin, Evans, & Choo, 2015). Prior literature has investigated whether and how ESNs positively impact knowledge sharing in organizations. For instance, an ESN’s shared goals significantly contribute to a person's volition to share knowledge (Chow & Chan, 2008). Oostervink, Agterberg, and Huysman (2016) observe that knowledge workers can effectively use ESNs for knowledge sharing through connection, reputation, and information management. Interpreting the complex inter-relationships of knowledge workers engaging in knowledge-sharing activities, Leonardi (2015) shows how ESNs can increase the accuracy of people's meta-knowledge in organizations.

Recent studies identify some important factors that significantly influence knowledge sharing in ESNs. For instance, an ESN's affordances can shape knowledge-sharing activities through factors such as social capital dynamics, relationship support, context collapse, and network interactions (Ellison, Gibbs, & Weber, 2015). Factors, such as knowledge self-efficacy, social interaction ties, and the norm of reciprocity, have a positive impact on knowledge-sharing activities and knowledge workers' individual job performance in ESN environments (Kwahk & Park, 2016). Researchers have identified social interaction, experience sharing, information relationship and networking, observation, and mutual trust as requirements for individuals to create and share tacit knowledge in ESNs (Panahi, Watson, & Patridge, 2012). The characteristics of knowledge workers with respect to their knowledge, access, engagement, and safety in ESNs can improve their ability to create and share knowledge. Although the literature discusses many behavioral factors, it has not thoroughly studied incentives for knowledge sharing in ESNs, which we focus on in this paper.

2.3 Incentives for Knowledge Sharing

Incentives play an important role in facilitating knowledge sharing in knowledge management systems by fostering a knowledge-sharing culture (Szulanski, 1996), by streamlining knowledge management processes (Argote, McEvily, & Reagans, 2003), and by sustaining the development of knowledge initiatives (Baird & Henderson, 2001). Recent research continues to confirm the importance of incentives in promoting knowledge sharing in organizations. For instance, Wang, Noe, and Wang (2014) found that workers will engage in knowledge-sharing activities more if they know that they will be evaluated and rewarded for doing so. Lee, Shiue, and Chen (2016) argue that top management should design and provide appropriate incentive mechanisms to motivate workers to share their knowledge to achieve process improvements. Fullwood and Rowley (2017) found that rewards significantly impact the attitude of knowledge sharing in academics and suggest that leaders need to associate rewards with knowledge sharing. Although researchers have studied incentives in broad contexts, they have not studied incentives for knowledge sharing in ESNs in detail.

While prior research has explored the inter-relationships between ESNs, knowledge sharing, and many factors that influence whether workers share knowledge, few studies have investigated how to best design incentive policies to facilitate knowledge sharing in ESNs. Our research makes significant contributions by exploring the design and efficacy of various individual and group incentive policies to facilitate knowledge sharing in ESNs. We consider different incentive schemes that target either specific workers or groups based on connectivity, efficiency, or both.

3 Model

We present a stylized model that captures ESNs' characteristics, workers' knowledge levels, and workers' connectivity and efficiency to analyze the organizational problem of designing incentive schemes to facilitate knowledge sharing in ESNs.

We consider an ESN that a firm uses to facilitate knowledge sharing among N knowledge workers. Following a network model approach, we model the ESN as a network of nodes with connecting links—a node represents each knowledge worker, and a link between two nodes represents the connection between the two corresponding workers (Jackson & Wolinsky, 1996; Friedman, Burns, & Cao, 2014). We treat knowledge in this context as skills that workers already have and can improve by learning. While knowledge is necessarily multi-dimensional, we simplify the model by considering knowledge as a one-dimensional entity for tractability as in prior research (e.g., Sundaresan & Zhang, 2012; d'Aspremont, Bhattacharya, & Gérard-Varet, 1998).

Workers in the network have different levels of knowledge. Researchers commonly consider knowledge levels as the "degree of coherence in an individual's knowledge" (Akbar, 2003), which an individual can develop through the process of gradual learning at different stages, which include "complete ignorance, awareness, measure, control of the mean, process capability, process characterization, know why, and complete knowledge" (Bohn, 1994). To operationalize the knowledge level, one can use financial or score-card methods, reflected through different indicators (Matošková, 2016). For example, Ghatasheh (2015) suggests that, in e-learning environments, the time people spend in reading online content along with the progress they make can be a good indicator of their knowledge level. As is common in prior literature (e.g., Fulk & Yuan, 2013; Sundaresan & Zhang, 2016), we consider that a knowledge provider incurs a cost for sharing knowledge. Since external incentives can motivate workers to participate (Connolly & Thorn, 1990) and help offset a worker's sharing cost, the firm can offer incentives for knowledge providers in the network.

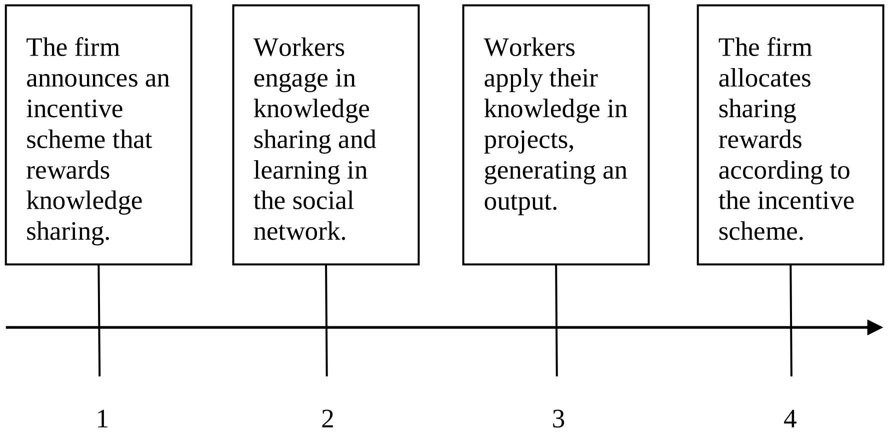

Figure 1. Model Timeline

Figure 1 summarizes the four stages in the model. We assume that all the information is transparent, which implies that the sharing costs and the network structure are observable. For instance, Leonardi (2015) argues that using an ESN helps organizations to improve workers' meta-knowledge about the network. First, the firm announces an incentive scheme to reward knowledge sharing. Second, workers share knowledge and learn through the social network. Third, workers work on projects, which generates output. Finally, the firm allocates sharing rewards to knowledge providers in the network based on the pre-announced incentive scheme.

To simplify our analysis, we assume the firm has two types of knowledge workers: high-knowledge and low-knowledge workers who have high (k^H) or low (k^L) knowledge levels. Higher knowledge levels play a role in enhancing a worker's ability, and the organizational output collectively depends on the knowledge levels of all workers. As recent work has identified, high-knowledge workers assume roles such as "answer person", "distributed expert", "discussion replier", or "value-added user", whereas low-knowledge workers may take the role of a "questioner", "distributed novice", "discussion starter", or "initiator" in an ESN (Viol, Bernsmann, & Riemer, 2016). In addition, we differentiate high-knowledge workers based on the high (C^H) or low (C^L) sharing costs they incur in sharing knowledge, but we assume no sharing costs for low-knowledge workers. Various factors such as time commitment (Ragsdell, Espinet, & Norris, 2014), knowledge complexity (McIver & Wang, 2016), technology fluency (Bruce, 1999), loss of authority (Michailova & Husted, 2003), compliance and performance evaluation (Busco, Frigo, Giovannoni, Riccaboni, & Scapens, 2005), and information security (Safa & Von Solms, 2016) influence this sharing cost. Since connectivity is an important consideration in ESNs (Huang & Liu, 2017), we use θ_x to denote the number of followers for a knowledge worker x on the network. Although recent literature on lurking (Cranefield, Yoong, & Huff, 2015) identifies interactions outside the network may mean even low connectivity or passive workers are valuable, we only consider the interactions in the ESN in this paper. The firm designs the incentive scheme $s(\cdot)$ based on the type of the knowledge worker and the number of her followers (the network structure); that is, $s(\cdot) = s_x(k_x, \theta_x, C_x)$, where $x = 1, 2, ..., N$, $k_x = k^H \, or \, k^L$, and $C_x = C^H \, or \, C^L \, or \, 0$.

In summary, the firm needs to design the incentive scheme $s(\cdot)$ to maximize its net benefits facilitated by knowledge sharing in the ESN:

$$\max_{s(\cdot)} \pi = f(K') - \sum_{x=1}^{N} s_x(k_x, \theta_x, C_x), \tag{1}$$

subject to

$$s_x(k_x, \theta_x, C_x) - C_x \geq 0, \tag{2}$$

where K' is the vector that represents the knowledge level of each worker after knowledge sharing (i.e., $K' = \{k_1', k_2', ..., k_n'\}$) and $f(K')$ measures the contributions of workers' knowledge to the firm's output. Appendix A summarizes the notation.

4 Analysis and Discussion

In this section, we present the results and discuss their implications. We first show a simplified model of the firm's decision problem and the corresponding solution for individual incentive policies and then explore the design and efficacy of five group incentive policies that target either specific workers or groups based on connectivity, efficiency, or both.

4.1 Incentive Policies for Individual Workers

We show more details of the model to facilitate our analysis. Using a network representation, we model the ESN with nodes that represent the workers and arcs that represent the "following" between workers. For instance, if a worker has five arcs that emanate out, five workers follow this worker's posts in the ESN. We use *I* as the index for the *m* high-knowledge workers ($i \in I = \{1, 2, ...m\}$), *j* as the index for the *n* low-knowledge workers ($j \in J = \{1, 2, ...n\}$), and ϕ_{ij} (1 and 0) as the connection status between worker *i* and *j* (where 1 and 0 represent being connected and disconnected, respectively). The number of followers (low-knowledge workers) for a high-knowledge worker *i* is:

$$\omega_i = \sum_{j \in J} \phi_{ij} \tag{3}$$

We define α_i and β_j as the knowledge-benefit factors for a high- (*i*) and a low-knowledge worker (*j*), respectively. We can model the net effect of the contribution of high- and low-knowledge workers with $\alpha_i k^H$ and $\beta_j k^L$. In the model, we let μ_j denote the learning indicator variable for a low-knowledge worker *j*; a low-knowledge worker will learn if at least one of the worker's connected high-knowledge worker shares knowledge. μ_j is given by:

$$\mu_j = \begin{cases} 1 & if \sum_{i=1}^{m} \phi_{ij} \lambda_i > 0, \\ 0 & otherwise. \end{cases} \tag{4}$$

High-knowledge workers decide whether to share their knowledge based on the incentive scheme announced. In this analysis, we assume that low-knowledge workers will learn whatever is shared with them and enhance their knowledge level to k^H. Therefore, the incentive scheme will target just the high-knowledge workers. Consequently, the firm's decision problem (P) can be shown as follows:

$$\text{(P)} \qquad \max_{s_i, \lambda_i} \left\{ f\Big(\sum_{i=1}^{m} \alpha_i k^H + \sum_{j=1}^{n} \beta_j \left[k^H \mu_j + k^L (1 - \mu_j) \right]\Big) - \sum_{i=1}^{m} s_i \right\}, \tag{5}$$

subject to, $\forall i \in I$, and $\forall j \in J$,

$$\mu_j \leq \sum_{i=1}^{m} \phi_{ij} \lambda_i, \tag{6}$$

$$s_i - \lambda_i C_i \geq 0 \quad , \tag{7}$$

$$\lambda_i, \mu_j \text{ binary variables.} \tag{8}$$

For ease of analysis, we assume that $f(z) = z$ and that any sharing benefits the firm. The following result shows the incentive payments to high-knowledge workers.

Lemma 1: The optimal incentive $s_i^* = \lambda_i C_i$, $\forall i = 1, 2, ..., m$.

Proof: Please see Appendix B.

We first explore the benchmark case (ESN with no overlap) in which each low knowledge worker is at most connected with one high-knowledge worker. The following proposition demonstrates how the incentive scheme should be designed for high-knowledge workers in such an ESN.

Proposition 1: In an ESN with no overlap such that $\forall j \in J, \sum_{i \in I} \phi_{ij} \leq 1$, the firm should offer an incentive to each high-knowledge worker covering the worker's sharing cost.

Proof: Please see Appendix B.

Proposition 1 indicates that, in the special situation when each low-knowledge worker can only learn from one high-knowledge worker, all the high-knowledge workers should be rewarded so that all the learners will learn.

We next investigate the second benchmark case (ESN with complete overlap) in which each low knowledge worker is connected to all high-knowledge workers. The incentive scheme for this case is shown in the following proposition.

Proposition 2: In an ESN with complete overlap such that $\forall j \in J, \sum_{i \in I} \phi_{ij} = m$, the firm should offer an incentive to a single low-cost high-knowledge worker covering the worker's sharing cost.

Proof: Please see Appendix B.

Proposition 2 suggests the solution for the special case when every low-knowledge worker follows all the high-knowledge workers. In this case, each of the high-knowledge workers can cover the entire network of low-knowledge workers. Therefore, the firm needs only offer incentive to a single high-knowledge worker to enable all the low-knowledge workers to learn and improve their knowledge levels.

Following the discussion of two special cases, we next show the algorithm to solve the firm's decision problem (P) in a general ESN.

Proposition 3: The following algorithm (A) will find a solution for the firm's decision problem (P).

Algorithm (A): Define Ω as the set of high-knowledge workers who will be offered an incentive, and Δ as the set of low-knowledge workers connected with the high-knowledge workers in Ω.

1. Set $\pi = 0$, $\Omega = \varnothing$ and $\Delta = \varnothing$
2. Do until $\Omega = I$ or $\Delta = J$ or ($\phi_{ij} = 0, \forall j \in J - \Delta$ and $\forall i \in I - \Omega$)

   a. $\Gamma = \arg\max_i \left\{ \sigma_i = \left[f(\pi + \sum_{j \in J - \Delta} \beta_j k^H \mu_j) - f(\pi) \right] \Big/ C_i \,\middle|\, \forall i \in I - \Omega, \lambda_i = 1 \right\}$

   b. $\forall i \in \Gamma$, $\lambda_i = 1$, $s_i = C_i$, $\Omega = \Omega \cup \{i\}$, and $\Delta = \Delta \cup \{ j \mid j = J - \Delta, \phi_{ij} = 1\}$

c. $\pi = \sum_{i\in\Omega} \alpha_i k^H + \sum_{j\in\Delta} \beta_j k^H$

3. $s_i^* = C_i, \forall i \in \Omega$

Proof: Please see Appendix B.

In the algorithm, we use the set Ω to store the indexes of the high-knowledge workers who are offered an incentive and Δ to store the indexes of the low-knowledge workers who are connected to those high-knowledge workers in Ω. Beginning with an empty set of both Ω and Δ, the ratio σ_i is calculated for each high-knowledge worker $i \in I$. σ_i measures the ratio of the marginal benefit that the firm gains from worker *I*'s knowledge sharing to all *I*'s followers (that are currently not in Δ) to the cost (which is the incentive the firm offers worker *i* to motivate the worker to share knowledge). The worker with the highest ratio will be included in Ω, and the set Δ will be updated accordingly to incorporate the new learners. If multiple high-knowledge workers have the same ratio, then one of them will be randomly selected as the worker to be included in Ω for the current iteration. The current total benefit for the firm is based on the high-knowledge workers in Ω and the low-knowledge workers in Δ. The steps of computing the ratio for each high-knowledge worker not in Ω, ranking all the ratios, identifying a worker with the highest ratio, and then including the worker in Ω will continue until one of the following conditions is met: all the high-knowledge workers are included in Ω, all the low-knowledge workers are in Δ, or there is no connection between low-knowledge workers not in Δ and any high-knowledge workers. Finally, the set Ω captures the high-knowledge workers who should be offered an incentive to share their knowledge.

We next demonstrate several examples and how our proposed algorithm can help find the solutions. For these examples, we construct an ESN with 32 low-knowledge workers and eight high-knowledge workers (four low cost and four high cost). We used Neo4j graph database (Neo4j, n.d.) to create all the example graphs.

4.1.1 Example Case 1: ESN with No Overlap

When each low-knowledge worker (shown in red color) is only connected to a single high-knowledge worker (shown in blue color) (see Figure 2), we apply the algorithm (A) to calculate the ratio σ_i for each high-knowledge worker in each iteration (see Appendix B for the complete solution procedure). Since there is no overlap between high-knowledge workers in terms of the low-knowledge workers they are connected to, the ratio σ_i for each high-knowledge worker is the same in each iteration. Since the four low-cost high-knowledge workers have a lower ratio than the four high-cost workers, the four low-cost workers will be selected first during the iterations followed by the high-cost workers. Finally, the incentives are $s_5^* = s_6^* = s_7^* = s_8^* = C_L$ and $s_1^* = s_2^* = s_3^* = s_4^* = C_H$; that is, the low-cost high-knowledge workers (H5, H6, H7, and H8) will be offered an incentive C_L, and high-cost high-knowledge workers (H1, H2, H3, and H4) will be rewarded with C_H.

4.1.2 Example Case 2: ESN with Complete Overlap

When each low-knowledge worker (red) is connected to all the high-knowledge workers (blue) (see Figure 3), only one iteration is necessary to identify the high-knowledge worker to be incentivized because each high-knowledge worker covers all the low-knowledge workers (see Appendix B for the complete solution procedure). The ratio is the same for workers H5, H6, H7, and H8, which is lower than the ratio for workers H1, H2, H3, and H4. Therefore, the firm only needs to offer an incentive to one of the low-cost high-knowledge workers (H5, H6, H7, and H8) to cover the entire network of low-knowledge workers. The incentive is $s_i^* = C_L (i = 5, 6, 7, or\ 8)$.

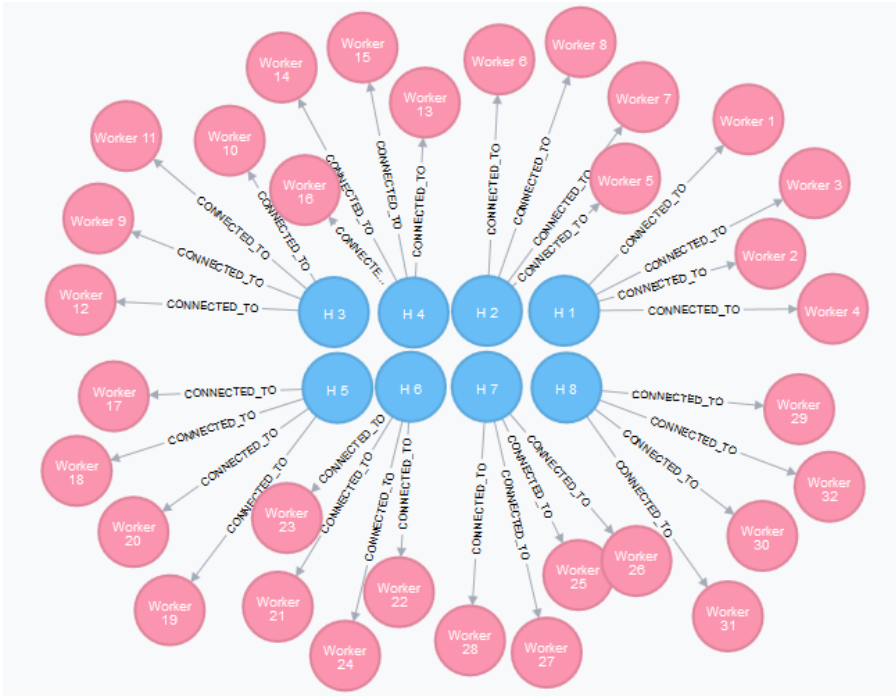

Figure 2. Case 1: ESN with No Overlap

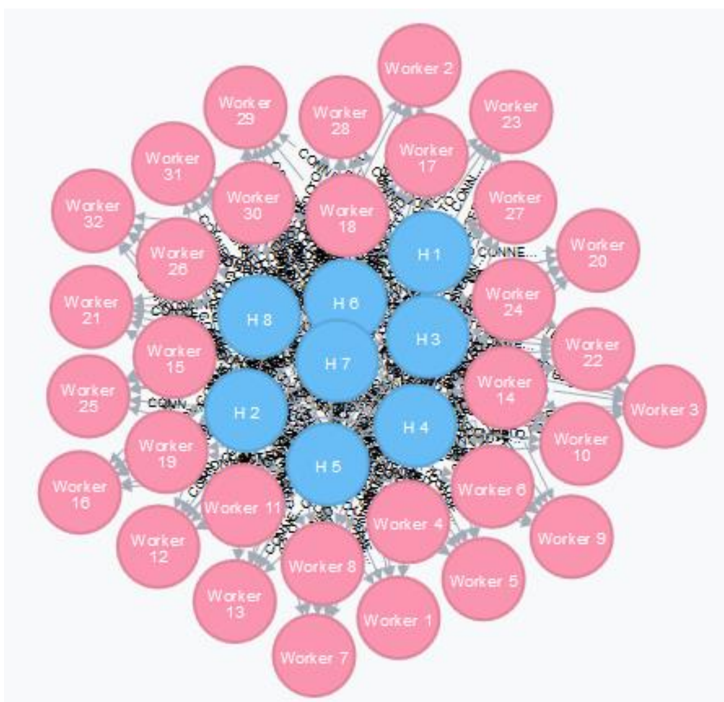

Figure 3. Case 2: ESN with Complete Overlap

4.1.3 Example Case 3: ESN with Partial Overlap

When each low-knowledge worker (red) is not connected to all the high-knowledge workers (blue) and same low-knowledge workers are connected to different high-knowledge workers (see Figure 4), several iterations are needed to identify which high-knowledge workers should be offered an incentive and the amount (see Appendix B for the complete solution procedure). The ratio is the same for workers H5, H6, H7, and H8, which is lower than the ratio for workers H1, H2, H3, and H4. Therefore, the firm can pick any one of the low-cost high-knowledge workers (H5, H6, H7, and H8) and offer the worker an incentive in the amount of C_L in the first iteration. Assume worker H5 is chosen in the first iteration, there will be only two candidates (H7 and H8) in the second iteration since there are only four new low-knowledge workers connected to H6. Assuming H7 is chosen in the second iteration, H1, H2, and H3 will be the candidates in the third iteration because they all have the same ratio. If H1 is picked in this iteration, then H3 will be selected in the last iteration. Finally, the incentive is $s_i^* = C_i, \forall i \in \Omega = \{1,3,5,7\}$.

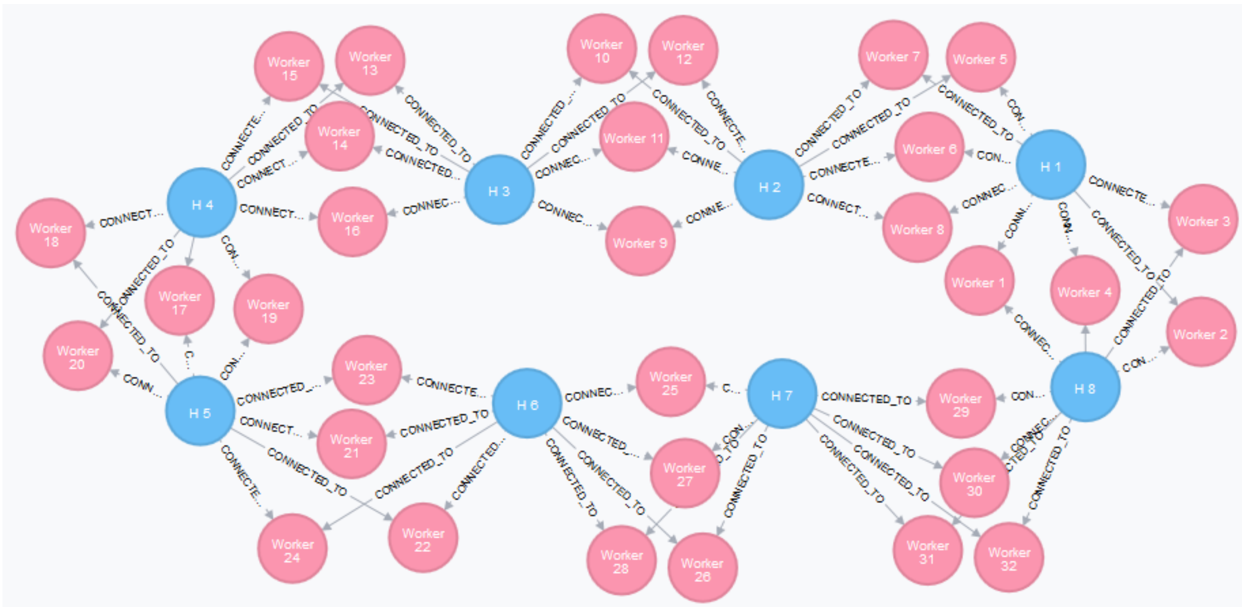

Figure 4. Case 3: ESN with Partial Overlap

4.2 Design of Group Incentive Policies

In Section 4.1, we demonstrate how a firm can offer incentives to high-knowledge workers individually. However, both business practice (APQC, 2015) and academic research (Siemsen et al., 2007) highlight the importance of group incentives for effective knowledge management. Therefore, we need to design group policies to incent knowledge sharing for groups of high-knowledge workers. In this section, we propose five group incentive polices and investigate their performance.

Table 1. Four Types of High-knowledge Workers

Types of a high-knowledge worker		Connectivity level	
		High	**Low**
Sharing cost	**Low**	Active and efficient (AE)	Passive and efficient (PE)
	High	Active and inefficient (AI)	Passive and inefficient (PI)

We categorize high-knowledge workers into two groups with either a low or high connectivity level similar to the two groups (high- or low-influence) that Miller and Christakis (2011) identify. Therefore, all the high-knowledge workers will fall into one of four categories in Table 1.

The active-efficient (AE) high-knowledge workers are those who are active in the ESN and are adept in sharing their knowledge over the network. In contrast, the active-inefficient (AI) and passive-efficient (PE) workers represent two groups of high-knowledge workers who are 1) active in the ESN but inefficient in sharing their knowledge and 2) efficient in sharing their knowledge but inactive in the ESN. Finally, the passive-inefficient (PI) high-knowledge workers do not actively participate in the network and are inefficient in coding and sharing their knowledge.

Targeting different groups of high-knowledge workers, we formulate the following five different group incentive policies.

1) **RA incentive policy (reward all)**: high-knowledge workers will be rewarded in the amount of C_H for sharing their knowledge over the ESN.

This policy captures all four types of high-knowledge workers because the incentive amount C_H is sufficient to compensate the sharing cost for both high-cost and low-cost high-knowledge workers. In addition, this policy does not differentiate based on the connectivity level of a high-knowledge worker.

2) **RE incentive policy (reward efficiency)**: high-knowledge workers will be rewarded in the amount of C_L for sharing their knowledge over the ESN.

This policy targets all the low-cost high-knowledge workers without differentiating their connectivity level. The inefficient high-knowledge workers will be reluctant to share their knowledge because their sharing costs C_H will not be sufficiently compensated by the incentive amount C_L that this policy offers.

3) **RC incentive policy (reward connectivity)**: high-knowledge workers with a high connectivity level will be rewarded in the amount of C_H for sharing their knowledge over the ESN.

This policy targets the high-knowledge workers with a high connectivity level without differentiating based on their sharing costs. Both high-cost and low-cost high-knowledge workers with be compensated in the amount of C_H for their sharing.

4) **REC incentive policy (reward efficiency and connectivity jointly)**: high-knowledge workers with a high connectivity level will be rewarded in the amount of C_L for sharing their knowledge over the ESN.

This policy rewards only low-cost high-knowledge workers with a high connectivity level. High-cost high-knowledge workers with a high connectivity level will not be able to participate as the incentive amount C_L is not enough to cover their sharing cost.

5) **RBPI incentive policy (reward all but the passive and inefficient group)**: combination of RE and RC incentive policies.

This policy captures all high-knowledge workers except those with a high sharing cost and a low connectivity level. Since high-knowledge workers with a high connectivity level will be rewarded the amount C_H, low-cost, high-knowledge workers will receive an award C_H if they have a high connectivity level according to RC policy, whereas those with a low connectivity level will only receive an award C_L according to RE policy.

We assume that, among all the high-knowledge workers, p percent have a high connectivity level and q percent have a low sharing cost. Hence, the number of high-knowledge workers in each group is: AE (pqm), AI ($p(1-q)m$), PE ($(1-p)qm$), and PI ($(1-p)(1-q)m$). Next, let r denote the percentage of low-knowledge workers connected to high-knowledge workers with a high connectivity level and v as the percentage of those connected to high-knowledge workers with a low sharing cost. Then, the number of low-knowledge workers connected to each group of high-knowledge workers is: AE (rvn), AI ($r(1-v)n$), PE ($(1-r)vn$), and PI ($(1-r)(1-v)n$). In addition, we define a uniqueness factor ($\rho_{AE}, \rho_{AI}, \rho_{PE}, \rho_{PI}$) for each group to represent percentage of unique low-knowledge workers following each high-knowledge worker group. For instance, among the low-knowledge workers that are connected to the AE group, $1-\rho_{AE}$ percent of them are also connected to other groups of high-knowledge workers. For ease of analysis, we consider all the uniqueness factors to be the same (i.e., $\rho_{AE} = \rho_{AI} = \rho_{PE} = \rho_{PI} = \rho$). We calculate and show the total benefits and costs for all group incentive policies in Table 2. Note that the total benefit shown includes only the additional benefit from low-knowledge workers' learning.

Table 2. Total Benefit and Cost for Each Group Incentive Policy

Policy	Total benefit	Total cost
RA incentive policy	$n\beta k^H$	mC_H
RE incentive policy	$(1-\rho(1-v))n\beta k^H$	qmC_L
RC incentive policy	$(1-\rho(1-r))n\beta k^H$	pmC_H
REC incentive policy	$(1-\rho(1-rv))n\beta k^H$	$pqmC_L$
RBPI incentive policy	$(1-\rho(1-r)(1-v))n\beta k^H$	$pmC_H+(1-p)qmC_L$

The following propositions show that each incentive policy can perform the best for an ESN under different conditions.

Proposition 4: RE incentive policy performs the best among the five group incentive policies under the following conditions: $\frac{\rho n\beta k^H}{mC_L} > \max\left\{\frac{q(1-p)}{v(1-r)}, \frac{q-p}{v-r}\right\}$, $v > r$, and $\frac{\rho n\beta k^H}{mC_L} < \min\left\{\frac{1-q}{1-v}, \frac{p(1-q)}{r(1-v)}\right\}$.

Proof: Please see Appendix B.

Proposition 4 demonstrates that the "reward efficiency" policy will be the best when the ratio of the expected benefit and cost (for rewarding at a low-cost level) is within a certain range. One can observe that, when $v=0$, it will be impossible for RE policy to be the best policy, which implies that, if no low-knowledge workers are connected to low-cost high-knowledge workers, rewarding efficiency will not be a good incentive policy. When s approaches 1, the following corollary shows that RE policy may be the best policy.

Corollary 4: When $v=1$ and $q \le p$, RE incentive policy performs the best among the five polices.

Proof: Please see Appendix B.

Corollary 4 shows that, when all the low-knowledge workers are connected to low-cost high-knowledge workers, provided that the percentage of low-cost high-knowledge workers is lower than that of high-knowledge workers with a high connectivity level, RE incentive policy will be the best one among all five policies.

Proposition 5: RC incentive policy performs the best among all the group incentive policies under the following conditions: $\frac{\rho n\beta k^H}{mC_L} > \max\left\{\frac{p(1-qC_L/C_H)}{r(1-v)}, \frac{p-q}{r-v}\right\}$, $r > v$, and $\frac{\rho n\beta k^H}{mC_L} < \min\left\{\frac{1-p}{1-r}, \frac{q(1-p)}{v(1-r)}\right\}$.

Proof: Please see Appendix B.

Proposition 5 demonstrates that the "reward connectivity" policy dominates the other policies under certain conditions. One can observe that, when $r=0$, it will be impossible for RC incentive policy to be the best policy, which implies that, if no low-knowledge workers are connected to high-knowledge workers with a high connectivity level, rewarding connectivity will not be a good incentive policy. The following corollary demonstrates that RC incentive policy can be the best policy among all five policies under some simple conditions.

Corollary 5: When $r=1$ and $p \le q$, RC incentive policy performs the best among all the five polices.

Proof: Please see Appendix B.

Corollary 5 demonstrates that, when all the low-knowledge workers follow high-knowledge workers with a high connectivity level, if the percentage of high-knowledge workers with a high connectivity level is lower than that of high-knowledge workers with a low sharing cost, then RC policy will always be the best one among all five policies.

Proposition 6: REC incentive policy performs the best among all five group incentive policies under the following conditions: $\frac{\rho n\beta k^H}{mC_L} < \min\left\{\frac{1-pq}{1-rv}, \frac{q(1-p)}{v(1-r)}, \frac{p(1-q)}{r(1-v)}, \frac{p+q-2pq}{r+v-2rv}\right\}$.

Proof: Please see Appendix B.

Proposition 6 shows that, when r and v both approach one, all the low-knowledge workers are connected to the group of high-knowledge workers with a low sharing cost and a high connectivity level, which indicates that REC policy will likely perform the best among all five policies.

In addition, when the uniqueness factor ρ decreases, the left-hand-side of the condition becomes smaller, which increases the likelihood of the condition to hold. In other words, when an ESN becomes more overlapped, it is better to use REC policy to achieve the best performance. When the uniqueness factor approaches 0, an ESN will converge to a completely overlapped ESN in which REC policy is always the best among all five policies, which Corollary 6 shows.

Corollary 6: For an ESN with complete overlap, REC incentive policy performs the best among all the group incentive policies.

Proof: Please see Appendix B.

For an ESN with complete overlap, a high-knowledge worker in each group is connected to all low-knowledge workers. Therefore, the benefits that the firm can derive from the low-knowledge workers are the same for all five incentive policies. Since REC policy has the lowest cost, it is the best one among all the group incentive policies. One can also observe that RA policy performs the worst under these conditions.

Proposition 7: RBPI incentive policy performs the best among all the group incentive policies under the following conditions: $\frac{\rho n\beta k^H}{mC_L} < \frac{(1-p)(1-q)}{(1-r)(1-v)}$ and $\frac{\rho n\beta k^H}{mC_L} > \max\left\{\frac{q(1-p)}{v(1-r)}, \frac{p(C_H/C_L-q)}{r(1-v)}, \frac{pC_H/C_L+q-2pq}{r+v-2rv}\right\}$.

Proof: Please see Appendix B.

Proposition 7 demonstrates that RBPI policy may also be the one with the best performance under certain conditions. As the uniqueness factor ρ approaches 0, the conditions in the proposition are unlikely to be satisfied; so, RBPI policy will be less likely to be the best one, which is consistent with the finding in Corollary 6. In addition, when $r = v = 1$, the conditions in this proposition cannot be satisfied; hence, RBPI policy cannot perform better than other policies, which aligns with the result in Proposition 6.

Proposition 8: RA incentive policy performs the best among all five group incentive policies under the following conditions: $\frac{\rho n\beta k^H}{mC_H} > \max\left\{\frac{1-pqC_L/C_H}{1-rv}, \frac{1-p}{1-r}, \frac{1-qC_L/C_H}{1-v}, \frac{(1-p)(1-qC_L/C_H)}{(1-r)(1-v)}\right\}$.

Proof: Please see Appendix B.

Proposition 8 indicates that the “reward all” incentive policy can also be the best one of all five policies under certain conditions. However, when $r = v = 1$, it is impossible for the condition to hold, which implies that, if all the low-knowledge workers are connected to those high-knowledge workers with a low sharing cost and a high connectivity level, RA policy can never be the best policy. For this case, Proposition 6 suggests that REC policy is the one with the best performance.

5 Conclusion

Prior research has recognized the important role of social networks in knowledge management, but it has not explored how to best design incentives in ESNs for knowledge sharing. We address this gap in this paper by studying the design of both individual and group incentive schemes for rewarding knowledge sharing in an ESN.

We develop an analytically tractable model of an ESN in which high-knowledge workers can share their knowledge and low-knowledge workers can learn to improve their knowledge. The model permits one to explore different individual and group incentive schemes to motivate high-knowledge workers to share their knowledge with their followers in the ESN to maximize the organizational total net benefit from the network.

Specifically, our research makes the following contributions. First, we develop a simple algorithm to help find a solution to how to best design individual incentives. The algorithm iteratively ranks each high-knowledge worker in terms of the benefit-to-cost ratio and rewards those workers with higher ratios. Second, we propose and explore five group incentive policies that reward 1) all, 2) efficiency, 3) connectivity, 4) efficiency and connectivity, or 5) all but the passive and inefficient group. Third, we show that each of these policies can perform the best under different conditions. For instance, “reward efficiency” is the best policy when all the low-knowledge workers are connected to low-cost high-knowledge workers and the percentage of low-cost high-knowledge workers is lower than that of high-knowledge workers with a high connectivity level. Similarly, as an ESN becomes more overlapped, which implies that low-knowledge workers share connections to common high-knowledge workers, it is better to use “reward efficiency and connectivity jointly” policy to achieve the best performance.

This study analyzes the design of incentive policies for promoting knowledge sharing in ESNs. Future research should broaden the scope of our modeling framework to comprehensively investigate other incentive schemes. For instance, the type of a knowledge worker may not be observable, which will change the design of incentives. One may also need to consider the incentives for learners to facilitate the entire knowledge transfer process. In addition, the incentives that firms offer may dynamically impact the network structure, which one can also consider when designing the incentive schemes. Furthermore, one can also incorporate the role of information technology along with incentives. Our research provides valuable insights for practitioners to implement appropriate incentive policies to promote knowledge sharing in ESNs.

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Appendix A: Summary of Notation

Table A1. Summary of Notation

Symbol	Meaning
α_i , β_j	Knowledge-benefit factor for a high-knowledge worker i, j
C^H, C^L	Sharing cost (high, low) for a high-knowledge worker
k^H, k^L	Knowledge levels of high- and low-knowledge workers
$f(\cdot)$	Contributions of workers' knowledge to the firm
i	Index for the high-knowledge workers
j	Index for the low-knowledge workers
K'	Vector representing the knowledge level of each worker after sharing and learning
m	Number of high-knowledge workers
n	Number of low-knowledge workers
p	Percentage of high-knowledge workers with a high connectivity level
q	Percentage of high-knowledge workers with a low sharing cost
r	Percentage of low-knowledge workers connected to high-knowledge workers with a high connectivity level
v	Percentage of low-knowledge workers connected to high-knowledge workers with a low sharing cost
ρ	Uniqueness factor: percentage of unique low-knowledge workers following each high-knowledge worker group.
ϕ_{ij}	Connection status between worker *i* and *j*
$s(\cdot)$	Incentive scheme for knowledge workers
θ_x	Number of followers for a knowledge worker x
μ_j	Learning indicator for a low-knowledge worker *j*
x	Index for high or low type

Appendix B. Proofs

Proof of Lemma 1

Proof: Suppose $s_i \neq \lambda_i \mu_i$, then the firm can always reduce the amount of the incentive s_i to improve its total payoff.

Proof of Proposition 1

Proof: When each low knowledge worker is at most connected with one high-knowledge worker, $\lambda_i = 1$, $\forall i = 1, 2, ..., m$. Therefore, from Lemma 1, we know that $s_i = C_i$, $\forall i = 1, 2, ..., m$.

Proof of Proposition 2

Proof: When each low knowledge worker is connected with all high-knowledge worker, $\omega_i = n$, $\forall i = 1, 2, ..., m$. Therefore, a single high-knowledge worker can cover all low-knowledge workers to help them improve their knowledge levels.

Proof of Proposition 3

Proof: Following the steps in Algorithm [A], the firm can rank each high-knowledge worker i with respect to σ_i and offer an incentive to a worker with the highest ratio σ_i, and then re-rank all the remaining high-knowledge workers until all the low-knowledge workers are covered, all the high-knowledge workers are assigned an incentive, or all the remaining low-knowledge workers have no connections.

Solution Procedure for Case 1 with No Overlap

1. Set $\pi = 0$, $\Omega = \varnothing$ and $\Delta = \varnothing$

2.

Iteration 1

a. $\Gamma = \{5, 6, 7, 8\}$

b. $\lambda_5 = 1$, $s_5 = C_L$, $\Omega = \{5\}$, and $\Delta = \{17, 18, 19, 20\}$

Iteration 2

a. $\Gamma = \{6, 7, 8\}$

b. $\lambda_6 = 1$, $s_6 = C_L$, $\Omega = \{5, 6\}$, and $\Delta = \{17, 18, 19, 20, 21, 22, 23, 24\}$

Iteration 3

a. $\Gamma = \{7, 8\}$

b. $\lambda_7 = 1$, $s_7 = C_L$, $\Omega = \{5, 6\}$, and $\Delta = \{17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28\}$

Iteration 4

a. $\Gamma = \{8\}$

b. $\lambda_8 = 1$, $s_8 = C_L$, $\Omega = \{5, 6, 7, 8\}$, and $\Delta = \{17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32\}$

Iteration 5

a. $\Gamma = \{1, 2, 3, 4\}$

b. $\lambda_1 = 1$, $s_1 = C_H$, $\Omega = \{1,5,6,7,8\}$, and
$\Delta = \{1,2,3,4,17,18,19,20,21,22,23,24,25,26,27,28,29,30,31,32\}$

Iteration 6

a. $\Gamma = \{2,3,4\}$

b. $\lambda_2 = 1$, $s_2 = C_H$, $\Omega = \{1,2,5,6,7,8\}$, and
$\Delta = \{1,2,3,4,5,6,7,8,17,18,19,20,21,22,23,24,25,26,27,28,29,30,31,32\}$

Iteration 7

a. $\Gamma = \{3,4\}$

b. $\lambda_3 = 1$, $s_3 = C_H$, $\Omega = \{1,2,3,5,6,7,8\}$, and
$\Delta = \{1,2,3,4,5,6,7,8,9,10,11,12,17,18,19,20,21,22,23,24,25,26,27,28,29,30,31,32\}$

Iteration 8

a. $\Gamma = \{4\}$

b. $\lambda_4 = 1$, $s_4 = C_H$, $\Omega = \{1,2,3,4,5,6,7,8\}$, and
$\Delta = \{1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23,24,25,26,27,28,29,30,31,32\}$

Iteration 9

$\Omega = I$, loop stops

3. $s_i^* = C_i, \forall i \in \Omega = \{1,2,3,4,5,6,7,8\}$

Solution Procedure for Case 2 with Complete Overlap

1. Set $\pi = 0$, $\Omega = \varnothing$ and $\Delta = \varnothing$

2.

Iteration 1

a. $\Gamma = \{5,6,7,8\}$

c. $\lambda_5 = 1$, $s_5 = C_L$, $\Omega = \{5\}$, and
$\Delta = \{1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23,24,25,26,27,28,29,30,31,32\}$

Iteration 2

$\Delta = J$, loop stops

3. $s_5^* = C_L$

Solution Procedure for Case 3 with Partial Overlap

1. Set $\pi = 0$, $\Omega = \varnothing$ and $\Delta = \varnothing$

2.

Iteration 1

a. $\Gamma = \{5,6,7,8\}$

b. $\lambda_5 = 1$, $s_5 = C_L$, $\Omega = \{5\}$, and $\Delta = \{17,18,19,20,21,22,23,24\}$

Iteration 2

a. $\Gamma = \{7,8\}$

b. $\lambda_7 = 1$, $s_7 = C_L$, $\Omega = \{5,7\}$, and $\Delta = \{17,18,19,20,21,22,23,24,25,26,27,28,29,30,31,32\}$

Iteration 3

a. $\Gamma = \{1,2,3\}$

b. $\lambda_1 = 1$, $s_1 = C_H$, $\Omega = \{1,5,7\}$, and
$\Delta = \{1,2,3,4,5,6,7,8,17,18,19,20,21,22,23,24,25,26,27,28,29,30,31,32\}$

Iteration 4

a. $\Gamma = \{3\}$

b. $\lambda_3 = 1$, $s_3 = C_H$, $\Omega = \{1,3,5,7\}$, and
$\Delta = \{1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23,24,25,26,27,28,29,30,31,32\}$

Iteration 5

$\Omega = I$, loop stops

3. $s_i^* = C_i, \forall i \in \Omega = \{1,3,5,7\}$

Proof of Proposition 4

Proof: For RE incentive policy to be the best among all five polices, the following decision problem can be formulated:

$$\max_{p,q,r,v} \ (1-\rho(1-v))n\beta k^H - qmC_L$$

s.t.

$$(1-\rho(1-v))n\beta k^H - qmC_L > n\beta k^H - mC_H,$$

$$(1-\rho(1-v))n\beta k^H - qmC_L > (1-\rho(1-r))n\beta k^H - pmC_H,$$

$$(1-\rho(1-v))n\beta k^H - qmC_L > (1-\rho(1-rv))n\beta k^H - pqmC_L,$$

$$(1-\rho(1-v))n\beta k^H - qmC_L > (1-\rho(1-r)(1-v))n\beta k^H - pmC_H - (1-q)pmC_L,$$

$$p,q,r,v \ge 0.$$

The four constraints can be rewritten as:

$$\rho n\beta k^H / mC_L < (1-q)/(1-v),$$

$\rho n\beta k^H / mC_L > (q-p)/(v-r)$ and $v > r$,

$$\rho n\beta k^H / mC_L > q(1-p)/[v(1-r)],$$

$$\rho n\beta k^H / mC_L < p(1-q)/[r(1-v)].$$

When $\frac{\rho n\beta k^H}{mC_L} > \max\left\{\frac{q(1-p)}{v(1-r)}, \frac{q-p}{v-r}\right\}$, $v > r$, and $\frac{\rho n\beta k^H}{mC_L} < \min\left\{\frac{1-q}{1-v}, \frac{p(1-q)}{r(1-v)}\right\}$, all four constraints are satisfied, yielding a feasible solution for the problem.

Proof of Corollary 4

Proof: When $v=1$, the conditions can be reduced to $\frac{\rho n\beta k^H}{mC_L} > \frac{q-p}{1-r}$, which is always true when $q \le p$.

Proof of Proposition 5

Proof: For RC incentive policy to be the best among all five polices, the following decision problem can be formulated:

$$\max_{p,q,r,v} \ (1-\rho(1-r))n\beta k^H - pmC_H$$

s.t.

$$(1-\rho(1-r))n\beta k^H - pmC_H > n\beta k^H - mC_H,$$

$$(1-\rho(1-r))n\beta k^H - pmC_H > (1-\rho(1-v))n\beta k^H - qmC_L,$$

$$(1-\rho(1-r))n\beta k^H - pmC_H > (1-\rho(1-rv))n\beta k^H - pqmC_L,$$

$$(1-\rho(1-r))n\beta k^H - pmC_H > (1-\rho(1-r)(1-v))n\beta k^H - pmC_H - (1-p)qmC_L,$$

$$p, q, r, v \ge 0.$$

The four constraints can be rewritten as:

$$\rho n\beta k^H / mC_H < (1-p)/(1-r),$$

$$\rho n\beta k^H / mC_H > (p-q)/(r-v) \text{ and } r > v,$$

$$\rho n\beta k^H / mC_H > p(1-qC_L/C_H)/[r(1-v)],$$

$$\rho n\beta k^H / mC_H < q(1-p)/[v(1-r)].$$

When $\frac{\rho n\beta k^H}{mC_L} > \max\left\{\frac{p(1-qC_L/C_H)}{r(1-v)}, \frac{p-q}{r-v}\right\}$, $r > v$, and $\frac{\rho n\beta k^H}{mC_L} < \min\left\{\frac{1-p}{1-r}, \frac{q(1-p)}{v(1-r)}\right\}$, all four constraints are satisfied, yielding a feasible solution for the problem.

Proof of Corollary 5

Proof: When $r=1$, the conditions can be reduced to $\frac{\rho n\beta k^H}{mC_L} > \frac{p-q}{1-v}$, which is always true when $p \le q$.

Proof of Proposition 6

Proof: For REC Incentive Policy to be the best among all five polices, the following decision problem can be formulated:

$$\max_{p,q,r,v} \ (1-\rho(1-rv))n\beta k^H - pqmC_L$$

s.t.

$$(1-\rho(1-rv))n\beta k^H - pqmC_L > n\beta k^H - mC_H,$$

$$(1-\rho(1-rv))n\beta k^H - pqmC_L > (1-\rho(1-v))n\beta k^H - qmC_L,$$

$$(1-\rho(1-rv))n\beta k^H - pqmC_L > (1-\rho(1-r))n\beta k^H - pmC_H,$$

$(1-\rho(1-rv))n\beta k^H - pqmC_L > (1-\rho(1-r)(1-v))n\beta k^H - pmC_H - (1-p)qmC_L$,

$p,q,r,v \geq 0$.

The four conditions can be rewritten as:

$\rho n\beta k^H / mC_L < (1-pq)/(1-rv)$,

$\rho n\beta k^H / mC_L < q(1-p)/[v(1-r)]$,

$\rho n\beta k^H / mC_L < p(1-q)/[r(1-v)]$,

$\rho n\beta k^H / mC_L < (p+q-2pq)/(r+v-2rv)$.

When $\frac{\rho n\beta k^H}{mC_L} < \min\left\{\frac{1-pq}{1-rv}, \frac{q(1-p)}{v(1-r)}, \frac{p(1-q)}{r(1-v)}, \frac{p+q-2pq}{r+v-2rv}\right\}$, all four constraints are satisfied, yielding a feasible solution for the problem.

Proof of Corollary 6

Proof: For an ESN with complete overlap, the total benefit and cost for each incentive policy in Table 1 can be simplified by assigning $\rho = 0$. When $\rho = 0$, the condition in Proposition 6 will always hold, so REC incentive policy performs best among all five policies.

Proof of Proposition 7

Proof: For RBPI incentive policy to be the best among all five polices, the following decision problem can be formulated:

$$\max_{p,q,r,v} \; (1-\rho(1-r)(1-v))n\beta k^H - pmC_H - (1-p)qmC_L$$

s.t.

$(1-\rho(1-r)(1-v))n\beta k^H - pmC_H - (1-p)qmC_L > n\beta k^H - mC_H$,

$(1-\rho(1-r)(1-v))n\beta k^H - pmC_H - (1-p)qmC_L > (1-\rho(1-v))n\beta k^H - qmC_L$,

$(1-\rho(1-r)(1-v))n\beta k^H - pmC_H - (1-p)qmC_L > (1-\rho(1-r))n\beta k^H - pmC_H$,

$(1-\rho(1-r)(1-v))n\beta k^H - pmC_H - (1-p)qmC_L > (1-\rho(1-rv))n\beta k^H - pqmC_L$,

$p,q,r,v \geq 0$.

The four conditions can be rewritten as:

$\rho n\beta k^H / mC_L < (1-p)(1-q)/[(1-r)(1-v)]$,

$\rho n\beta k^H / mC_L > p(C_H / C_L - q)/[r(1-v)]$,

$\rho n\beta k^H / mC_L > q(1-p)/[v(1-r)]$,

$\rho n\beta k^H / mC_L > (pC_H / C_L + q - 2pq)/(r+v-2rv)$.

When $\frac{\rho n\beta k^H}{mC_L} < \frac{(1-p)(1-q)}{(1-r)(1-v)}$ and $\frac{\rho n\beta k^H}{mC_L} > \max\left\{\frac{q(1-p)}{v(1-r)}, \frac{p(C_H / C_L - q)}{r(1-v)}, \frac{pC_H / C_L + q - 2pq}{r+v-2rv}\right\}$, all four constraints are satisfied, yielding a feasible solution for the problem.

Proof of Proposition 8

Proof: For RA incentive policy to be the best among all five polices, the following decision problem can be formulated:

$$\max_{p,q,r,v} \; n\beta k^H - mC_H$$

s.t.

$$n\beta k^H - mC_H > (1-\rho(1-v))n\beta k^H - qmC_L ,$$

$$n\beta k^H - mC_H > (1-\rho(1-r))n\beta k^H - pmC_H ,$$

$$n\beta k^H - mC_H > (1-\rho(1-rv))n\beta k^H - pqmC_L ,$$

$$n\beta k^H - mC_H > (1-\rho(1-r)(1-v))n\beta k^H - pmC_H - (1-p)qmC_L ,$$

$$p,q,r,v \ge 0 .$$

The four conditions can be rewritten as:

$$\rho n\beta k^H / mC_H > (1-qC_L/C_H)/(1-v) ,$$

$$\rho n\beta k^H / mC_H > (1-p)/(1-r) ,$$

$$\rho n\beta k^H / mC_H > (1-pqC_L/C_H)/(1-rv) ,$$

$$\rho n\beta k^H / mC_H > (1-p)(1-qC_L/C_H)/[(1-r)(1-v)] .$$

When $\dfrac{\rho n\beta k^H}{mC_H} > \max\left\{\dfrac{1-pqC_L/C_H}{1-rv}, \dfrac{1-p}{1-r}, \dfrac{1-qC_L/C_H}{1-v}, \dfrac{(1-p)(1-qC_L/C_H)}{(1-r)(1-v)}\right\}$, all four constraints are satisfied, yielding a feasible solution for the problem.

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